REACT: The Riskmap Evaluation and Coordination Terminal

by

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Submitted to the Department of Electrical Engineering and Computer Science
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Abstract

The United Nations Office for Disaster Risk Reduction (UNDRR) states that economic losses due to natural disasters have risen 151 percent in the past 20 years. Of these disasters, floods are the most common. The Sendai Framework for Disaster Risk Reduction was created by the UNDRR in order to chart goals for future risk mitigation; among its seven global targets is increasing the availability of disaster risk information and assessment systems. Disaster information systems use state of the art techniques such as remote sensing in order to mitigate damages from natural and man made hazards.

It is common in developed countries utilize networks of advanced sensors and ahead of time mapping in order to facilitate emergency responses; however, such systems are not available in developing countries due to cost limitations. The widespread proliferation of smart phones and social media use in developing countries means that citizens can be used as sensors by reporting disaster information online. The Riskmap system was developed by the Urban Risk Lab at MIT in order to gather citizen report streams. Such citizen disaster reports have two issues: a large influx of reports can cause information overload in emergency operations centers, which makes it difficult to summarize the situation. Machine learning has previously been used in order to analyze and simplify information for human consumption. This work seeks to use novel machine learning techniques to fully utilize crowd-sourced social media reports gathered using the Riskmap system.

Thesis Supervisor: Miho Mazereeuw
Title: Associate Professor

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Chapter 1

Introduction

Flooding is the most common natural disaster in the world [1]. Flood related deaths account for half of all deaths from natural disasters [2]. Although flooding impacts both developed and developing countries, developing nations face much worse consequences as a result of flooding since they lack resources to adequately mitigate hazards [3]. Deltaic megacities in developing countries are particularly at risk because of unregulated urbanization, rising population and climate change are increasing the rate at which floods occur [1]. In addition to the increase in disaster risk, there is little data that is available before, during, and after a disaster to help stakeholders mitigate hazards [4]. Data scarcity makes it hard to pinpoint where to direct aid during disasters and where to make infrastructure improvements after disasters [5].

Various stakeholders have different but overlapping interests with regards to disaster management. Government and NGOs work together to provide relief and mitigate damages from flooding [6], while Citizens look for relevant flood information and try to reduce their risk [7]. Information is at the core of this interaction; however, data scarcity makes it hard for emergency personnel to optimize their use of resources, while citizens have an abundance of information about their surroundings but must be careful not to trust incorrect or outdated information about broader areas [8]. The natural solution is for citizens on social media to submit real time reports to the Emergency Operations Center (EOC), which is tasked with using those reports to inform citizens. There is one problem with this solution, in times of crisis EOCs can suffer from information overload when they are presented with too much information [9].

The REACT system uses novel machine learning and human computer interaction research to reduce information overload in EOCs, thereby decreasing disaster response time. REACT classifies reports as indicating heavy flooding or not through an ensemble model. It first extracts key features from each of the parts of a report (text, picture, metadata) using known techniques and then uses a small dense neural net to classify the citizen report.

First we establish the motivation for using citizens as sensors and analyzing this noisy data using machine learning. We then review different machine learning techniques that have been used in crisis information systems, including those that also utilize social media. Finally a novel ensemble learning model is presented that can accurately predict large flood events from crowdsourced data.

Chapter 2

Background

Global climate change is 'expected to increase the frequency and intensity of floods' [10]. Urban areas are particularly at risk from flooding; unchecked development and rising population have created megacities that regularly experience flooding [1]. Nowhere is this more apparent than in South and Southeast Asia, where the severity of floods has been increasing over the past several decades [11].

Of the world's 33 megacities, over 60 percent are located in developing Asian Countries [12]. These cities face a looming crisis as flood risk increases, but there are also unique opportunities for risk mitigation. Megacities are characterized by high population density. This high density leads to an increase in economic damages and loss of life, but it also means that there are large numbers of citizens that have disaster information they would like to share with others [1].

2.1 History of Disaster Informatics

One of the best known and earliest work in mapping disasters was John Snow's use of maps to find the source of the 1857 Cholera outbreak in London[13]. This example is generally taught to all new students of epidemiology and illustrates the need not only for up to date information, but for systems that ease the analysis of this information. In John Snow's case, the map was the tool that allowed him to visualize the spread of the disease and effectively take action that ended the outbreak.

In more recent times, the need for Information Technology (IT) in disaster management has been clear since the mid 1980s when computers became user friendly enough to be used during disasters [14]. Now many EOCs use Geographic Information Systems (GIS), inventory control systems, and online messaging systems among other technology in order to organize spatial data and analyze disaster information. While some systems have helped some regions to better respond to disasters, researchers have often stated that 'there are many reasons to remain skeptical about the idea that technology will provide a panacea for emergency management problems' [15, 9, 16]. A number of potential negative effects associated with disaster management technology have been identified: the potential for the technology to increase social inequality, the potential of information overload, and the dissemination of incorrect and outdated information [8, 17].

2.1.1 Social Media and Disasters

The history of social media and the hashtag is invariably linked to disaster communication. It was during the San Diego bush fires of 2007 that the hashtag was first widely used on twitter [18].

Quarantelli emphaszied that 'management of hazards is fundamentally social in nature and not something that can be achieved strictly through technological upgrading' [9] yet social media brings human behavior into a machine readable format that can be used to provide further information during disasters.

Much work has been done in passively listening to social media streams in order to better understand how disasters unfold and how humans use social media as a communication tool during disaster events. Many of these studies use hand labeled tweets in order to classify what kind of information people talk about [19].

Further work has evolved to using artificial intelligence methods to automatically label new tweets using supervised learning. For example, Patrick Meier's Haiti Crisis Map initially used volunteers to classify large number of tweets, but his more recent projects focus on the use of AI for tackling big data problems [4].

2.1.2 Crowdsourcing vs. Passive Listening

> *Since humanitarian organizations don't ask eyewitnesses on social media to report information on needs and impact groups like the Red Cross have to rely on witnesses sharing relevant information by chance.*
>
> — Patrick Meier [4]

As Patrick Meier points out in *Digital Humanitarians*, passively listening to twitter data streams and hoping that someone posts relevant disaster information is not always a winning strategy. One solution to this problem is to have paid workers that collect information and enter it into disaster information systems as in [20], which details how paid workers were used to input data from citizens during the Mozambique floods of 2007; however, this method is expensive and does not scale well. The same report states that 'data processing and consolidation [were] difficult' and that 'the few data entry clerks struggled to keep up' [20].

Citizens as sensors Geosocial intelligence Holderness [21].

2.2 The Riskmap System

2.2.1 Need for open data

Creating bespoke information systems at the beginning of disasters has been the norm [20]; however this means that disaster response organizations must become acclimated with the system at the same time that they are dealing with disaster situations. Researchers have shown the need to create open sourced crowdsourced emergency systems that provide open data [22]. The Riskmap system was created to fill that need.

2.2.2 System Overview

The Riskmap system alleviates the load on emergency managers by centralizing reports from many social media sources. It also makes it easy not only for reports to

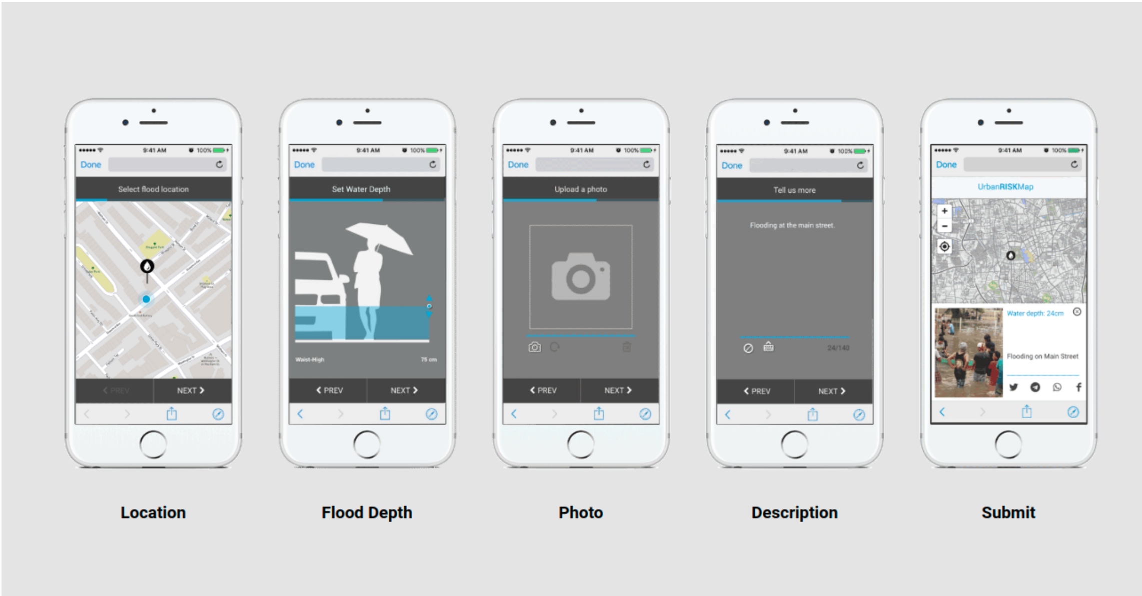

Figure 2-1: Submitting a flood report card

come into the response center, but also for emergency managers to indicate which areas of a city are most affected at any one time. The data gathered during an event is persistent and available under the Creative Commons license, which allows researchers to track the flood over time and pinpoint areas that are particularly vulnerable to flooding, thus fulfilling the need for open data [21].

Riskmap consists of many different social media bots that are actively filtering social media streams and looking for citizens that might be reporting flooding events, it then reaches out to those users and asks them to submit a flood report that consists of a GPS location, the estimated flood height at that location, a picture, and a textual description. These reports are then displayed on a public map for other citizens to inform themselves. Furthermore, EOC personnel are able to access the Risk Evaluation Matrix (REM), a special dashboard that allows them to give even more information to citizens.

The system has been in place in Jakarta and Chennai since 2016, and has seen hundreds of thousands of views during flood events.

2.3 Conquering Information Overload

It is not enough to create an advanced system for consuming citizen reports, it is also necessary to ensure that this system does not consume resources that are already scarce during a disaster event, for example the time of emergency workers [20]. It is also important to reduce the amount of time needed to create insights because if analyzing data takes too much time, then decision makers will make decisions without having fully analyzed the data [3].

Using computers to automatically make sense of disaster data has long been a goal in disaster informatics, but only recently have machine learning techniques become good enough to be implemented in production emergency systems [4]. Image recognition algorithms can provide summaries of objects and scenes found in user submitted photos [23, 24]. Natural language processing can estimate the probability that a textual document is overall negative or positive and thereby give EOCs a shorthand way to summarize thousands of reports in short amounts of time [23, 25]. Finally, ensemble learning methods can learn relationships between disparate datasets and synthesize a single result [26].

// lay out problem statement for thesis

Chapter 3

Previous Work

3.1 Machine Learning in Crisis Informatics

3.1.1 Passive Listening

Using social media in order to obtain on the ground information about disasters, both anthropogenic and otherwise, is as old social media itself. One of the first

The usefulness of social media

Most of the work in this area has been done by passively listening to twitter posts or facebook comments.

Some was looking for clues after disasters: [7] problem: don't have real time results

Some used humans to filter out social media for real time disaster info [27] [4]

Some involved using machine learning: [28]

Problems with that approach:

It is very difficult to filter out which social media images are related to the disaster and which are not.

3.1.2 On Image Data

Online learning using traditional transfer learning [24] but online (so they get people to label images as a disaster happens?) plus train with generic disaster images in order to solve cold start problem at the beginning of an event. Classify social media images into 3 classes: (severe, mild, little) damage. [29]

3.1.3 On Text Data

Crowd sentiment detection during disasters using twitter and the 2010 San Bruno CA fires n=3698 [25]

Feature engineering on twitter messages to classify into pre-incident, during incident and post-incident [30]

Classifying tweets as informative/ not informative using CNNs vs SVMs (CNN wins) [31]

CrisisNLP from the Qatar Computing Research Institute has a huge datasets [23]

3.1.4 Ensemble Data Models

This paper [26] uses deep learning to identify damage related info

Low level visual features (extract color, shape texture) + then Use bag of words on the text. Make a [32]

There have been some notable projects that attempt to provide complete systems that can be used for different disasters. Most notably are the Sahana and the AIDR projects.

Sahana has suspended its disaster response project that helped to mobilize volunteers to respond to disasters. // not focusing enough on the HCI and hidden wiring?

3.1.5 Common Difficulties

Task Subjectivity

Task subjectivity is an incredibly common issue [29, 3]. While most humans can agree on whether an object is or is not an apple, this task does not translate to defining if a picture indicates a severe event or a minor one.

In other words, people's perception of risk varies widely from region to region and from citizen to citizen [3].

Small Datasets

Although larger datasets have recently become available, there has historically been a scarcity of training and validation data available for Deep learning models that are trained on small datasets tend to overfit on the training data and do not generalize well to the validation dataset [33].

In many early studies only hundreds of data points were considered— combined with the small size of those data points (for example, twitter microblogs of 140 or 280 characters) and effectively using deep learning becomes very difficult. For example [25] only uses 3,698 tweets in order to train

Connects citizens to EOC

As discussed in 2.2, the Riskmap system helps to connect citizens to Emergency Operations Centers

Focus on technology rather than whole system design

A series of UN case studies on six disaster information systems found that while engineering and system design were essential, it was the hidden wiring of

> An important message emerges from the case studies: an effective disaster information management system requires a good technological platform, but also much more. Software programs for storing, sharing, and manipulating data for disasters are being developed or patched together at a steady pace, often in the aftermath of disasters. The real difficulty lies in anchoring these technological approaches in an appropriate institutional context where they are supported by relevant and effective operating procedures, agreed terminology and data labeling, and a shared awareness of the benefits of proper handling of disaster information. Clearly, a disaster information management system must be supported by accepted rules, procedures, and relationships that encourage, facilitate, and guide the production, sharing, and analysis and use of data in response to disaster.

In these case studies, the institutional dimension—the hidden wiring—determined the effectiveness of the systems. [20]

Chapter 4

Methodology

4.1 Data Description

The Riskmap system allows citizens to easily submit disaster reports 2.2; as such it has allowed the Urban Risk Lab at MIT to gather thousands of reports of real flooding in Indonesia and India.

4.1.1 Image Data

4.1.2 Text Data

4.1.3 Flood Height

4.1.4 Location Information

Chapter 5

Results

5.1 Individual

5.1.1 Image Data

5.1.2 Text Data

5.1.3 Flood Height

5.1.4 Location Information

5.2 Bagging

Appendix A

Tables

Table A.1: Armadillos

Armadillos	are
our	friends

Appendix B

Figures

Figure B-1: Armadillo slaying lawyer.

Figure B-2: Armadillo eradicating national debt.

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